A novel small-signal modeling and simulation technique in SiGe:C HBT for ultra high frequency applications

Gh. R. Karimi[a] **and R. Banitalebi**

Electrical Engineering Department of Razi University, Kermanshah, Iran

a) *ghkarimi@razi.ac.ir*

Abstract: In this paper the small-signal equivalent circuit model of SiGe:C heterojunction bipolar transistors (HBTs) has directly been extracted from S-parameter data. Circuit simulations by the use of neural network architecture and a standard IHP 0.13 um BiCMOS technology confirmed our design goals. To check the capability of the direct approach, scattering parameters were generated and compared with Artificial Neural Network (ANN). Then measured and model-calculated data have represented an excellent agreement with less than 0.166% discrepancy in the frequency range of $> 300\,\mathrm{GHz}$ over a wide range of bias points.

Keywords: small-signal, equivalent circuit model, SiGe:C, heterojunction bipolar transistor, ANN

Classification: Microwave and millimeter wave devices, circuits, and systems

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1 Introduction

The millimeter-wave (MMW) frequency spectrum, which spans from 30 to 300 GHz, is highly suitable for imaging and radar. MMW frequencies also have wavelengths, small enough to make them advantageous over microwave frequencies.

Only recently, advancements in silicon-germanium (SiGe) technology have produced devices with transit frequencies, capable of operating at MMW frequencies. Moving towards silicon will not only be cheaper but also allow greater integration between MMW circuits and the analog as well as digital processing circuits [1, 2].

It has been shown that adding carbon to the base of a SiGe HBT results in an excellent high-frequency noise behavior of the transistors [3].

SiGe:C BiCMOS technology is a strong contender for single-chip solutions for wireless and broadband communications systems. Various applicable fields such as high bit-rate optical network or automotive radar demand SiGe:C HBTs with fT/fmax above 150 GHz and high density CMOS to perform complex digital signal processing. This raises many devices and integration issues which will be discussed and illustrated in this paper using results of IHP 0.13 μm SiGe:C BiCMOS technology [4].

Most of the presented papers have dealt with the parameter extraction for the hybrid-T equivalent circuit and only few for the hybrid-π topology. Although the hybrid-T model is directly matched with the physics of the device, because the compact models such as SGP, VBIC, MEXTRAM, and HICUM, AgilentHBT, the most popular commercial circuit simulators, are based on the hybrid-π topology, so parameter extraction for the hybrid-π HBT model is much more important.

In this paper, the small-signal equivalent circuit model of SiGe:C HBTs has directly been extracted from S-parameter data [5].

Artificial neural networks are kind of patterning in order to process information, made by imitation of biological neural networks. When we want to approximate a function, one of the best options is MLP networks. Balancing weight, these networks produce the desired output. The following is a small-signal model of simulated SiGe:C HBT parameters with a MLP network in bias points and different frequencies.

2 De-embedding and extraction of elements

Small-signal equivalent circuit model for a modern SiGe:C HBT in the forward active region is shown in Fig. 1. This model is based on the well-known hybrid-π equivalent circuit which is a linearized version of the AgilentHBT compact model.

We divide this circuit into two parts: the inner part contains the bias-dependent intrinsic elements, and the outer part consists mostly of bias-independent extrinsic elements. The intrinsic base resistance is included in the equations, accurate extraction of resistance is very important to avoid any accumulated errors.

We have found that the error in resistance is originated from the pad de-embedding. So we have employed a correction procedure for the error originated by the pad de-embedding. This error is corrected by the S-parameter of the HBT at "over-driven I_B" (high forward bias) operation.
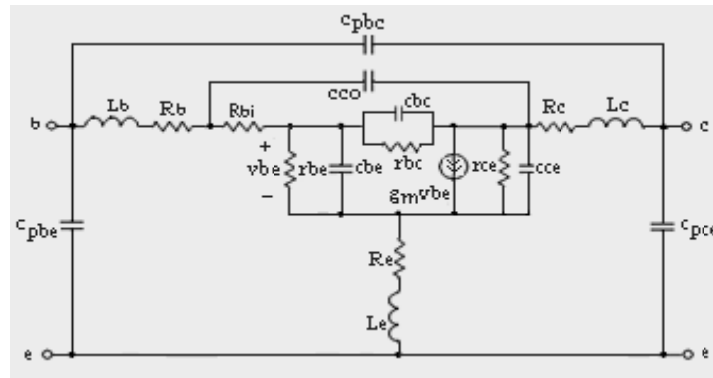

Fig. 1. Small-signal equivalent circuit model for a SiGe:C HBT.

2.1 Extraction of access resistances and inductances

In the similar way reported in [6], the extraction of parasitic elements is first made by biasing the device in "over-driven I_B" operation in order to extract the parasitic series resistances and correct the de-embedding.

These resistances and inductances can be described by the Z-parameters of this circuit by the following equations;

$$R_b = real\{Z_{11} - Z_{12}\} \tag{1}$$

$$R_e = real\{Z_{12}\} \tag{2}$$

$$R_c = real\{Z_{22} - Z_{21}\} \tag{3}$$

$$L_b = \frac{imag\{Z_{11} - Z_{12}\}}{\omega} \tag{4}$$

$$L_e = \frac{imag\{Z_{12}\}}{\omega} \tag{5}$$

$$L_c = \frac{imag\{Z_{22} - Z_{21}\}}{\omega} \tag{6}$$

The values of R_b, R_e, R_c, L_b, L_e and L_c can easily be determined from equations. The extracted R_b, R_e and R_c for the SiGe:C HBT are 20, 10, and 9.9 Ω, and we obtain L_b, L_e and L_c which are respectively equal to -0.002 pH, -0.365 pH, and -0.095 pH. These negative inductance values are as a result of the over-de-embedding of the probing pad parasitic. So these values must be corrected and set to zero values.

2.2 Extraction of parasitic capacitances

The overlap oxide capacitances can be extracted from HBT under "cold" operation. Under such conditions, the effects of series resistances, dynamic resistance, and transconductance are negligible compared with those of the capacitance elements.

$$\frac{imag\{Y_{12} - Y_{22}\}}{\omega} = C_{pce} \tag{7}$$

$$\frac{imag\{Y_{11} - Y_{12}\}}{\omega} = C_{pbe} + C_{be} \tag{8}$$

$$\frac{imag\{-Y_{12}\}}{\omega} = C_{pbc} + C_{bc} + C_{bo} \tag{9}$$

In Eq. (8) and Eq. (9), the parameters C_{pbe} and C_{pbc} are considered to be bias-independent, while C_{be} and $C_{bc} + C_{co}$ are bias-dependent elements. The extraction of the parasitic capacitances C_{pbe} and C_{pbc} are carried out by fitting the $C_{pbe} + C_{be}$ and $C_{pbc} + C_{bc} + C_{co}$ in the equation of $C_{j0} + C_j \left(1 - \left(\frac{V_j}{P_j}\right)\right)^{M_j}$. The extrapolated intercepts at the ordinate of these lines give the values of C_{pbe} and C_{pbc}. The obtained values of them are almost zero.

The value of C_{pce} can easily be determined from Eq. (7), The extracted amount is 0.15 fF.

2.3 Determination of Y-parameters of the intrinsic part of the hybrid-equivalent circuit

After the de-embedding and correction of the de-embedding error, we can get the admittance parameters (Y) of the device under test shown in Fig. 1.

To determine intrinsic circuit parameters, it is best to use Y-parameters for intrinsic device;

$$C_{be} = \frac{imag\{Y_{i11} - Y_{i12}\}}{\omega} \tag{10}$$

$$R_{be} = \frac{1}{real(Y_{i11} + Y_{i12})} \tag{11}$$

$$C_{bc} = \frac{imag(Y_{i12})}{\omega} \tag{12}$$

$$R_{bc} = -real(Y_{i12}) \tag{13}$$

$$C_{ce} = \frac{imag(Y_{i12} + Y_{i22})}{\omega} \tag{14}$$

$$R_{ce} = \frac{1}{real(Y_{i12} + Y_{i22})} \tag{15}$$

$$g_{m0} = \sqrt{((real(Y_{i21}) - real(Y_{i12}))^2 + ((imag(Y_{i12}) - imag(Y_{i12}))^2}$$

$$(16)$$

$$\tau = \frac{\sin^{-1}\left(\frac{imag(Y_{i21} - Y_{i12})}{g_m}\right)}{\omega} \tag{17}$$

Where $g_m = g_{m0}e^{-j\omega\tau}$.

$$R_{bi} = real\left(\frac{1}{Y_{i11}}\right)_{at\ high\ frequancy} \tag{18}$$

$$C_{co} = imag\left(\frac{Y_{i11} \times Y_{i22} - Y_{i12} \times Y_{i21}}{Y_{i11} + Y_{i21}}\right)/\omega - C_{bc} \tag{19}$$

3 Neural network architecture

Multilayer perceptrons (MLP), the most popular type of neural network used for microwave device modeling, have been demonstrated to be a robust modeling approach to predict microwave device behavior.

Each layer has a weight matrix, a bias vector b, and an output vector t. A smooth tan-sigmoid neuron activation function [7] has been used for each layer, defined by;

$$f(n) = \frac{2}{1 + e^{-2n}} - 1 \tag{20}$$

This function is bounded, continuous, monotonic, and continuously differentiable.

After implementation of this model, the simulation of transistor characteristics was performed to determine how well the model could reproduce the measured data. The intrinsic parameters were characterized over various operational regions of SiGe:C HBT.

In a neural network, bias points and frequencies are considered as input and intrinsic parameters as output. Neural network architecture used to model each intrinsic parameter has 3 inputs, 51 neurons in the hidden layer and 9 neurons in output layer.

In order to obtain required values of V_{CE} from $1\,V$ to $3.3\,V$ with the step $1.15\,V$, we have changed I_B from $25\,\mu A$ to $100\,\mu A$ with three points and the frequency from $1\,GHz$ to $350\,GHz$ with the step of $10\,GHz$. Using this neural network to simulate, we consider 75 percent of this data set as network training data and 25 percent of these data as network testing data.

In order to analyze network accuracy, we use error calculation. The root mean square test (RMS) error between extracted value from measurement and values predicted by ANN (Fig. 2 (a)) is less than 0.17% for all parameters over a range of bias points, showing that the neural network has been well trained.

To check the capability of the direct approach to predict HBT dynamic behavior, scattering parameters were generated using the scheme given in Fig. 1 [8], and them compared with values predicted by ANN (Tables I (a), I (b), Fig. 2 (b)). Furthermore, it shows the developed model has good generalization ability.

Table I. (a) Scattering parameters were generated using by ADS (b) ANN.

(a)

freq	S(1,1)	S(1,2)*20	S(2,1)*10	S(2,2)*20
1GHz	0.789-j0.108	1.749-j0.064	0.874-j0.032	0.852-j0.007
88.25GHz	-0.914-j0.325	0.726-j0.355	0.363-j0.177	0.755-j0.433
175.5GHz	-0.964-j0.178	0.59-j0.369	0.295-j0.185	0.584-j0.792
262.8GHz	-0.979-j0.126	0.481-j0.377	0.24-j0.188	0.36-j1.083
350GHZ	-0.987-j0.097	0.398-j0.368	0.199-j0.184	0.102-j1.315

(b)

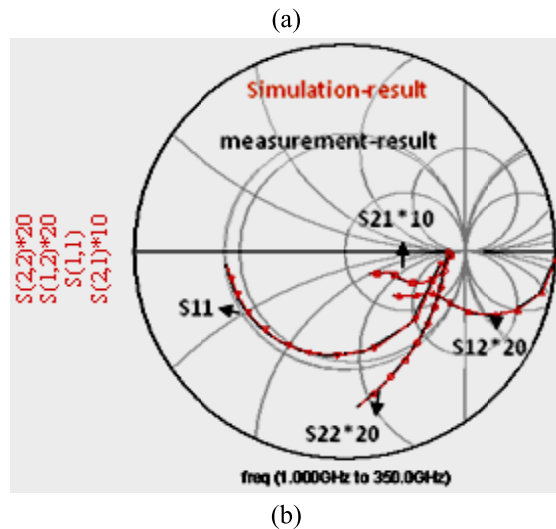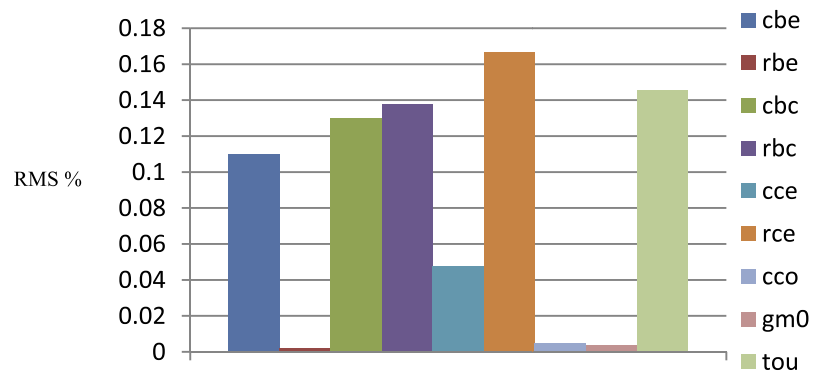| freq	S(1,1)	S(1,2)*20	S(2,1)*10	S(2,2)*20
1GHz	0.789-j0.108	1.751-j0.064	0.875-j0.032	0.851-j0.007
88.25GHz	-0.914-j0.324	0.726-j0.355	0.363-j0.178	0.754-j0.433
175.5GHz	-0.964-j0.178	0.59-j0.37	0.295-j0.185	0.583-j0.792
262.8GHz	-0.979-j0.126	0.481-j0.377	0.24-j0.188	0.359-j1.082
350GHZ	-0.987-j0.096	0.398-j0.368	0.199-j0.182	0.101-j1.314

(a)

(b)

Fig. 2. (a) The RMS test error (b) Comparison of measured data and values predicted by ANN for S-parameters $S11$, $S12$, $S21$, $S22$.

4 Conclusion

In this paper, an improved HBT small-signal parameter extraction technique is developed and applied to the SiGe:C HBT. Differing from the previous researches, this technique employs an accurate pad de-embedding with im-

proved method of extraction of g_{m0}, R_{be}, C_{be}. Therefore, we believe that the proposed extraction method is a simple and reliable routine, applicable for optimization of transistor design, process control, and the improvement of AgilentHBT compact model, especially for SiGe:C HBTs. This designed neural network model is superior to other models-based on table. In fact, using low memory, fast extraction of parameters and ability of extension are advantages of this model.